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Decision support for risks managers in the case of deliberate food contamination: The dairy industry as an example ☆

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ABSTRACT

Dairy farms were identified, which can be included in a contingency plan set up to prevent or mitigate the consequences of deliberate contamination of a food supply chain. The deliberate introduction of a contamination into the supply chain of milk was simulated in a scenario where milk producers serve as the entry sources and consumers of milk represent the target to be affected by the contamination. It is shown that the entry sources have an impact on the damage caused, i.e. in terms of the number of consumers reached. A contingency plan is provided that contains a list of entry sources ranked according to their impact on the damage to consumers. To generate this list, a computer program was developed that simulates the impact of the contaminations on consumers via the trade of contaminated milk. Possible variations in the trade links between milk producers, dairies and consumers as well as between dairies are considered. It is investigated how these trade links alter the generated list of entry sources.

The results indicate that, regardless of the actual milk trade flow, control measures should be introduced on 39% of the milk producers in order to minimize the damage. The identification of suitable entry sources may help risk managers to focus on these farms in a contingency plan that improves the sensitivity of control activities related to deliberate contamination.

1. Introduction

Risks in supply chains can come from a large number of sources [1–9] and thus their prevention leads to a broader view of risk management [10]. For example in the study of Wu and Olson [11], financed risks of enterprises were addressed and models were applied in order to support their investment decision-making [11]. Other studies estimated the risks of a food contamination in order to provide the risk-informed decision-making on food safety management issues [12,13]. However, Enterprise Risk and Enterprise Risk Management (ERM) have attracted a great deal of attention, especially in recent years [14]. But there are slightly different views on ERM [14,15]. In general, ERM is defined as a systematic and integrating approach to managing all risk factors which an organization is faced with [15] and thus represents the most effective way for companies to manage or mitigate their risks [10]. Besides [15], COSO [16] defines ERM as “a process [that is] effected by an entity's board of directors, management and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risk to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives”. Similarly, Olson and Wu [17] define ERM as “the integrated process of identification, analysis and either acceptance or mitigation of uncertainty in investment decision making”. Against this theoretical background, our research framework rests on the definition of risk management provided by [17] with a focus on the decision-making of supplier selection under consideration of their vulnerability to terrorist entry sources. The food supply chains are tempting targets for terrorists as attacks on these systems may destabilize the economy and disrupt the flow of foods [18]. Defense preparedness in this field is often in the hand of the private sector [19]. For example, companies in the food sector apply for certifications of their food defense management strategies [20]. Rasco and Bledsoe [19] claimed that about 80% of consumers consider the food supply as vulnerable to attacks. Several incidents of intentional contamination in the food supply chain underline its vulnerability [21–25]. For instance, at least 751 people were affected due to deliberate contamination of salad bars in Oregon, USA, in 1984 by members of a religious commune [25–27]. Another case occurred in 2003, where approximately 100 people were affected after consumption

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of ground beef that had been contaminated by a supermarket employee [25,28]. According to Sobel et al. [29], an intentional contamination of the food supply may be similar to an accidental contamination. In this context, the likely size of damage caused by an attack can be inferred from observed unintentional foodborne disease outbreaks [29]. In 1994, for example, a large outbreak of *Salmonella enteritidis* in the United States affected approximately 224,000 people after accidental contamination of pasteurized liquid ice cream [22,29,30].

However, the above mentioned studies are based on the assumption that the selection of the entry sources for a deliberate contamination of the supply chain can be random, because the consequences of deliberate of accidental contaminations cannot be distinguished from each other.

In this paper, we concentrate on the hypothetical threat posed by a deliberate introduction of a pathogen or toxins into the milk supply chain. We focus on a scenario, where the milk producer (dairy farm) is used as the entry source for a contamination and where milk consumers are the target of the attack [13]. We assume that a potential attacker would aim at reaching a maximum spread of the contaminated milk and at using a minimum number of milk producers as entry sources for the contamination. Ideally, the attacker would aim at reaching the maximal spread of contaminated milk by contaminating the first milk producer in the network of milk trade. If the attacker was not stopped after the first assault, he would contaminate another milk producer as a second entry source if this contamination cause larger increase of infected consumers compared to the first entry sources. The attacker has achieved his goal, when all consumers have been supplied with the contaminated milk. Due to the fact that the milk trade between milk producers, dairies and consumers as well as between dairies in the milk supply chain is dynamic [31,32], we hypothesize that trade links may influence the selection of milk producers that are used as the entry sources for the contamination by the attacker.

However, the most important task during a foodborne outbreak is to identify the source of the food contamination and its entry sources [33]. Thus, the aim of this paper is to provide the following information for risk managers on the chosen scenario: Firstly, which entry sources would be chosen by a hypothetical attacker, if data on the commodity flows became publicly available? Secondly, how many entry sources would the attacker have to choose to reach all consumers with contaminated milk in Germany? Thirdly, in which sequence would an attacker choose potential entry sources? Fourthly, are there milk producers who can be selected independent of the flow of milk to induce maximum damage? Fifthly, in the context of ERM, what strategies can be derived to prevent or mitigate the consequences of deliberate contamination with scant resources? These questions were answered by proposing a contingency plan.

To prevent that the results of this research are used as an instruction for a potential attacker, we work with highly aggregated and anonymous data. Moreover, we use a random gravity model to generate the trade connections between the actors in the milk supply chain. Furthermore, we focus on the spread of hypothetically contaminated milk via trade. Our investigation does take any features into account that are specific for particular milk producers, such as bio-security measures. Nevertheless, we expect that contamination of milk in dairy plants is less likely than in farms due to restricted access to the dairy plants. Relevant characteristics of milk, the kind of biological agents or toxins, individual dispositions like the age of people [34–37] and internal processes like pasteurization [38–43], which may influence the vulnerability of the consumers to contamination, but also the spread of contamination [32], are not considered in this paper.

2. Material and methods

2.1. The generation of the milk trade network

The underlying milk trade network has been described in detail elsewhere [32]. In brief, the term "milk trade network" comprises the trade connections between milk producers (P) and dairies (D), dairies and consumers (C) and the trade connections between dairies. On the one hand, the horizontal flow of milk between dairies (inter-dairy trade) and on the other hand, the vertical flow (without inter-dairy trade) between milk producers, dairies and consumers is taken into account. All milk producers of a country and all consumers of a municipality were aggregated into one milk producer node or one consumer node, respectively. The milk trade network consists of 12,597 nodes, with $P=294$, $D=80$ and $C=12{,}223$.

Data on the trade relations from milk producer nodes to dairy nodes are available in accordance with the German law of market regulations for goods (Marktordnungsmeldeverordnung). Information on the trade connections between dairy nodes and consumer nodes as well as between dairy nodes was not available and these trade connections were predicted through a standard randomized gravity model [32]. The standard randomized gravity model [44–47] was based on the assumption that the probability of two market actors trading with each other is proportional to the supply and demand of the respective actors and indirectly proportional to their distance to each other [32,46,48]. Further information on the generation of the German milk trade network can be found in [32]. However, different trade networks are required due to the random nature of the model [32]. One hundred different trade networks were therefore created, consisting of 50 trade networks with inter-dairy trade and 50 without inter-dairy trade.

2.2. Greedy algorithm and objective functions

To identify the number and the rank-order of milk producer nodes, which may cause maximum damage in terms of the number of contaminated consumer nodes, the greedy algorithm was used. This algorithm can solve optimization problems [49–51] and is applied under the predetermined objective function to find the most appropriate milk producer nodes (P) as entry sources for a contamination to cause maximum damage on the condition that maximum spread of contaminated milk in association with a maximum number of contaminated consumer nodes (C), so that the number of milk producer nodes involved in spreading the contamination is minimal (Eq. (1)).

$$\max \left|\{c : c \in C;\ \min\left|\ \{p : p \in P\}\right|, p \in D, c \in D, D \in R\}\right| \qquad (1)$$

In this context, there is a second condition requiring that trade connections between milk producer nodes and dairy nodes ($p \in D$) as well as between dairy nodes and consumer nodes ($c \in D$) exist. Furthermore, the condition should be reflexive and transitive (R), as trade connections between dairy nodes should be considered in our model. However, the objective function considers only the trade volume (v) and the trade connections of the milk producer nodes, their associated dairy nodes and the consumer nodes.

294 candidate of entry sources were hypothetically contaminated in the computer simulations, selected and sorted according to the extent of the resulting damage caused dependent on the respective milk trade flow.

The greedy algorithm starts with the identification of the candidate set of solutions. A candidate is selected for the solution when it maximizes the selection function. Let S represent the ordered set of selected candidates and s_i is a member of this ordered set at position i. Each member of the set is assigned a value $\Delta v(s_i)$. This value represents the additional weighted number of contaminated consumer nodes, when the milk producer node s is added to the set of solutions. The weight ($w_i = i^{-1}$) depends on the position (i) of the milk producer node in the ranked list of solutions ($i=1,\ldots,n$). With respect to the objective function, a milk producer node is only added to the list if $S_{i+1} > S_i$ with $S_i = \sum_i^n \Delta v(s_i\, w_i)$. Therefore, the greedy algorithm searches for the "best" milk producer node according to the number of contaminated consumer nodes, sets this milk producer node on the first position in the list of potential entry sources and then follows with the "next-best" milk producer node (Fig. 1). As a consequence, every place in the list can be filled by only one milk

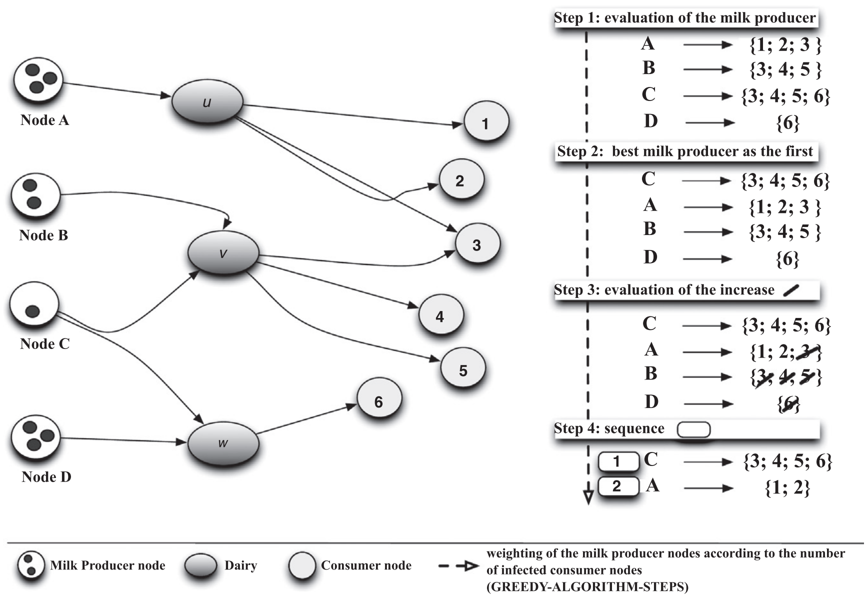


Fig. 1. Steps of the greedy algorithm (without inter-dairy trade).

producer node. The greedy algorithm cannot handle the theoretical case where two milk producer nodes have exactly the same value and should therefore occupy the same place in the list of potential entry sources.

The algorithm stops when S_i cannot be improved any more or, in other words, when all consumer nodes (C) are contaminated (Fig. 1). The scenario, in which all consumers are reached, represents a worst-case situation. The greedy algorithm was applied for two kinds of milk trade networks, one with inter-dairy trade and one without. We therefore obtained two contingency plans over 50 simulations for each kind of the milk trade network. One simulation represents one sub-trade network.

Step (1): Contamination of a milk producer node and calculating the number of consumer nodes that can be hypothetically contaminated (absolute); Step (2): Selecting the milk producer nodes that have reached the maximum number of consumer nodes. The milk producer node with the maximum number of infected consumer nodes was used as a baseline for further evaluations of milk producer nodes; Step (3): Select the second-best milk producer node, on the condition that it has infected other consumer nodes than the first milk producer node (maximum increase for the first milk producer node); Step (4): Sorting the milk producer nodes according to extent of damage leading to a rank-order of the milk producer nodes in the contingency plan.

To answer the question, whether milk producer nodes can be used regardless of the flow of milk as appropriate entry sources for a contamination, a comparison between the two contingency plans according to the most commonly observed portals of entry was conducted. To achieve a better comparison between the milk producer nodes, which may occur in both contingency plans, and those, which are only included in one of the contingency plans, the impact of these milk producer nodes for the damage situation was determined with Eq. (2).

$$I_{(p)} = \sum_{i=1}^{r} h(r)g(r) \tag{2}$$

The impact of milk producer nodes $I(p)$ is calculated using its rank (r) (position) in the ordered contingency plan determined by the greedy algorithm for each of the considered random networks. Let $h(r)$ be the frequency of (p) at position (r) using all simulation results, where $g(r)$ is a weight, $g(r)=(r+1)-i$. The value of r is determined by the greedy algorithm and resembles the maximum size (length of the contingency plan) of the best-ordered milk producer nodes in random network considered.

3. Results

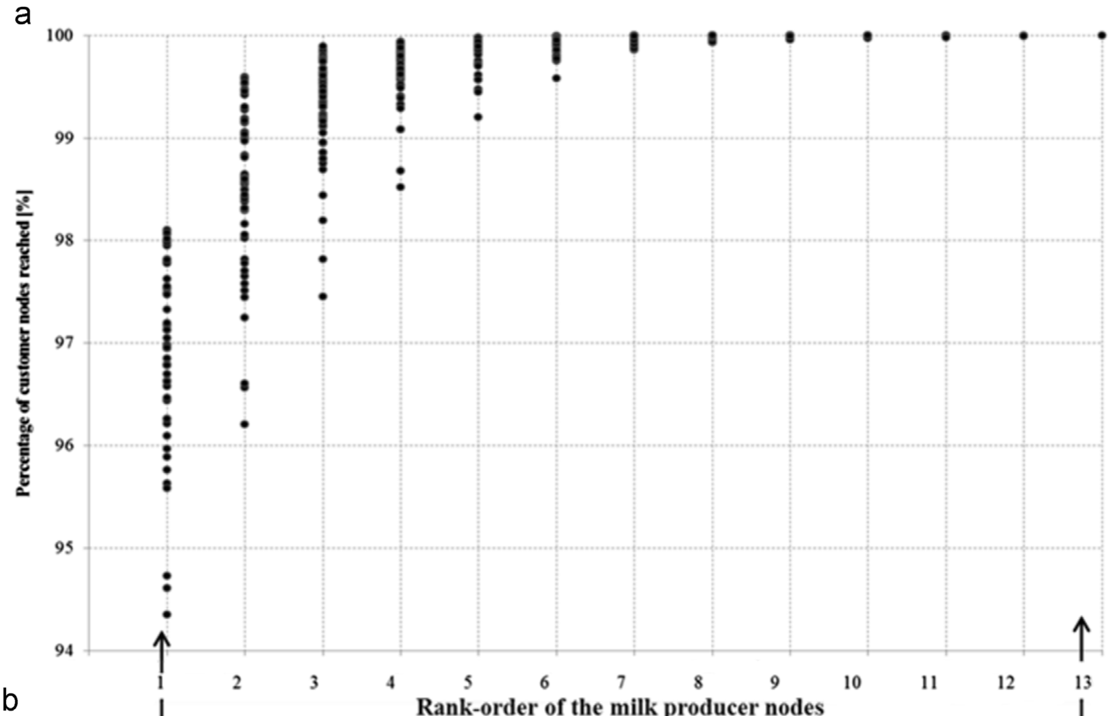
The contingency plan includes the number and rank-order of milk producer nodes for inducing the maximum damage situation as well as the associated number of contaminated consumer nodes (Figs. 2 and 3) for the two kinds of trade networks (with and without inter-dairy trade). In Figs. 2 and 3(b), each line represents a simulation process of a total of 50 simulations. Each line represents the number of milk producer nodes which are involved in the worst-case situation per simulation. Furthermore, each column shows the rank of the milk producer nodes for the worst-case situation according to the reached number of consumer nodes. Figs. 2 and 3(a) depict the damage situation in respect to hypothetically contaminated consumer nodes in association with the rank-order of the milk producer nodes.

When the inter-dairy trade structures are taken into account, the entire contingency plan includes 86 (29.2%) different milk producer nodes from a total of 294 (100%). For all 50 simulations, the greedy algorithm calculated that the minimum required number of milk producer nodes to achieve the worst-case situation was seven and that the maximum number of milk producer nodes was 13 (Fig. 2(b)). On average, by the introduction of a contamination into nine milk producer nodes a worst-case situation can be introduced. More than 94% of the consumer nodes could be contaminated upon introduction of the hypothetical pathogen or toxins into the milk producer nodes on the first rank of the contingency plan (Fig. 2(b)). The milk producer nodes on the second rank led to a further increase of the damage situation of 1–2% (Fig. 2(a)). All subsequent milk producer nodes induce a minimal increase in the number of contaminated consumer nodes by 1– 4%.

One milk producer node (ID: 294) was identified in 49 out of 50 simulations (Fig. 2(b)). Two milk producer nodes (ID: 66 and 500) showed up in 89% of all simulations. The remaining 83 milk producer nodes appeared on average 3.6 times in the simulations. In all simulations, 27 different milk producer nodes appeared only once (Fig. 2(b)).

One milk producer node (ID: 294) was on the first rank in 26 of 50 simulations (Fig. 2(b)). In all remaining simulations, this milk producer node ranked second ($n=13$) or third rank ($n=10$) in the contingency plan. Such “direct neighborhood” ranking of milk producer nodes in the contingency plan was observed for 68 (79.1%) nodes in all simulations (Fig. 2(b)).

If the inter-dairy trade is neglected, a worst-case situation could be caused on average by 18.4 (minimum 15, maximum 20) contaminated milk producer nodes (Fig. 3(b)). The contingency a



b

	1	2	3	4	5	6	7	8	9	10	11	12	13
S_1	252	294	299	509	518	14	66	500	26				
S_2	294	297	299	511	14	519	500	66	444	120			
S_3	294	297	11	14	527	66	273						
S_4	294	61	143	505	467	5	519	203	66				
S_5	294	61	467	517	155	500	273	66					
S_6	512	294	299	39	303	15	519	66	500	444			
S_7	294	512	98	75	268	14	120	66	500				
S_8	294	512	2	3	66	120	26						
S_9	513	294	299	2	57	14	66	500	273				
S_10	252	294	8	44	1	14	66	120	500				
S_11	294	252	464	21	519	500	66						
S_12	100	513	294	31	83	511	29	500	66				
S_13	513	294	68	299	3	66	500						
S_14	100	252	294	402	233	39	3	66	500	120	444		
S_15	252	294	33	15	77	516	66	444	500				
S_16	294	297	83	509	14	516	66	500	120	489	240		
S_17	297	294	44	510	29	83	3	500	66				
S_18	294	252	510	14	110	500	66						
S_19	100	297	294	300	153	299	66	500					
S_20	100	297	294	4	299	148	468	3	500	240	66	120	
S_21	100	297	520	505	514	2	3	66	273	120			
S_22	294	512	31	59	15	176	500	66					
S_23	61	294	555	299	6	120	66	500	328	26			
S_24	294	252	467	6	4	152	444	120	66				
S_25	294	513	300	510	15	500	120	154	66	444			
S_26	100	252	294	299	231	303	6	519	66	500	120		
S_27	294	80	299	33	3	31	66	120	528	500			
S_28	294	252	11	39	233	401	66	500	6				
S_29	512	294	299	6	500	120	77	66					
S_30	294	252	44	299	232	66	120	500					
S_31	294	252	299	68	66	500	431						
S_32	294	297	555	299	203	500	240	66					
S_33	294	512	148	231	98	66	444	500					
S_34	100	61	294	505	39	14	515	240	500				
S_35	294	512	4	299	233	500	489	66					
S_36	100	61	294	2	500	120	66						
S_37	294	297	222	299	57	500	66	120					
S_38	294	61	222	299	511	6	500	66					
S_39	100	61	294	299	232	517	120	500	489				
S_40	297	294	106	110	86	203	500	273					
S_41	100	512	294	300	17	299	5	444	66	499	500		
S_42	294	297	555	299	6	500	431						
S_43	294	297	110	299	1	468	66	6	500	444			
S_44	294	61	83	509	326	555	15	66	120	444	47	73	500
S_45	297	294	4	153	59	6	66	500					
S_46	294	61	31	152	3	500	120	66					
S_47	100	252	294	555	150	273	240	66					
S_48	294	252	2	299	33	66	444	500	120				
S_49	61	294	464	1	45	14	120	66	500	273			
S_50	513	294	299	555	59	6	66	444					

Fig. 2. Contingency plan taking inter-dairy trade into account in association with the hypothetically contaminated consumer nodes. (a) Size of the damage situation with respect to the number of hypothetically contaminated consumer nodes per rank-order of the milk producer nodes. Each point represents the damage caused by a milk producer node in the underlying column of 2b. (b) Results of a total of 50 simulations. Each line shows the number of milk producer nodes that are involved in the worst-case situation per simulation; each column shows the rank-order of the milk producer nodes for the worst-case situation according to reached number of consumer nodes. The milk producers on the first rank caused the maximum damage situation. The milk producer nodes on the second place caused the largest increase of infected consumer nodes compared to the first milk producer nodes.

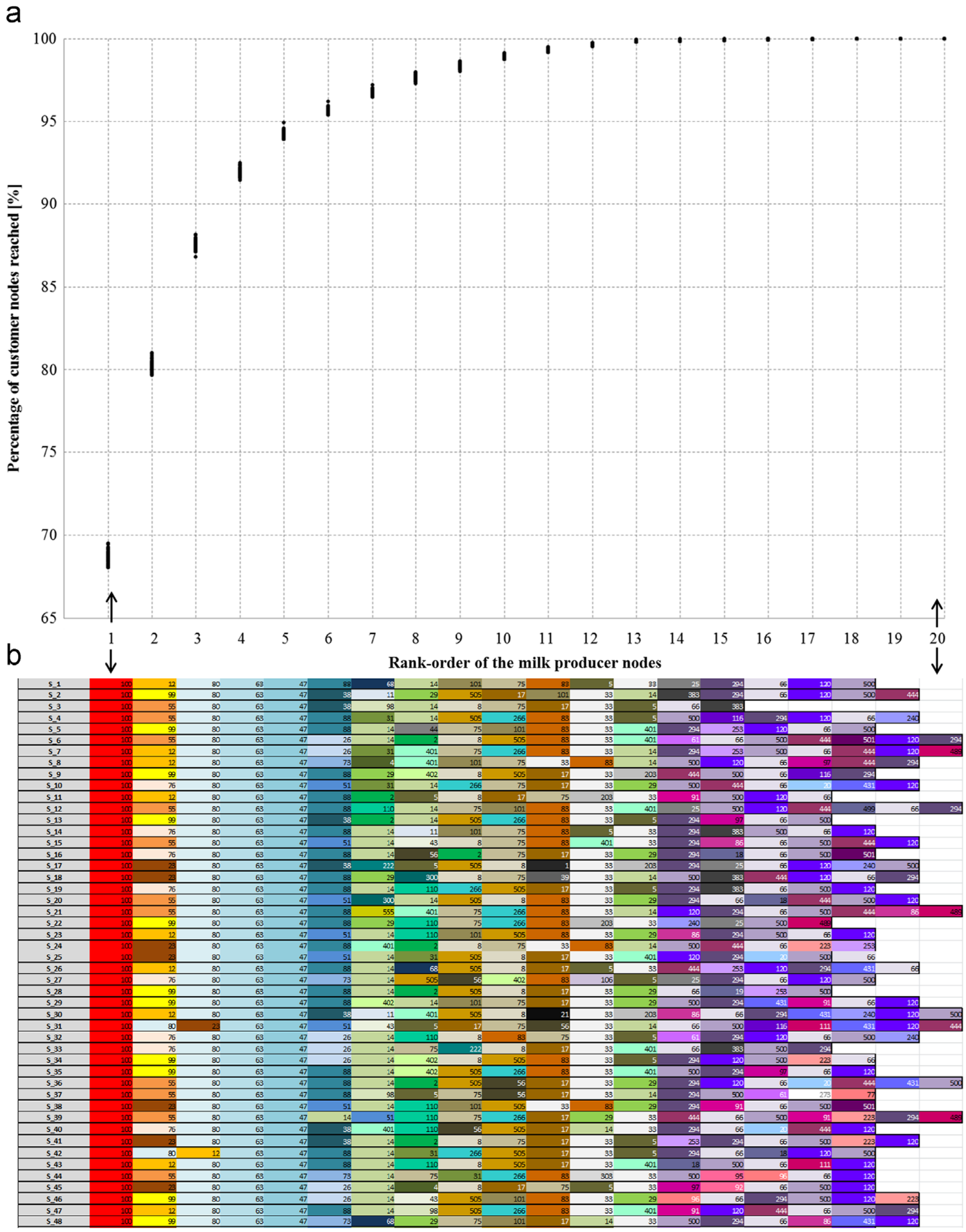


Fig. 3. The contingency plan without inter-dairy trade in association with the hypothetically contaminated consumer nodes. (a) Size of the damage situation with respect to the number of hypothetically contaminated consumer nodes per rank-order of milk producer nodes. Each point represents the damage caused by a milk producer node in the underlying column of 3b. (b) Results of 50 simulations. Each line shows the number of milk producer nodes that are involved in the worst-case situation per simulation; each column shows the rank-order of the milk producer nodes for the worst-case situation according to reached number of consumer nodes. The milk producers on the first rank caused the maximum damage situation. The milk producer nodes on the second place caused the largest increase of infected consumer nodes compared to the first milk producer nodes.

plan contained a total of 76 (25.8%) different milk producer nodes (Fig. 3(b)). The milk producer nodes with the highest rank in the contingency plan could infect more than 68% of all consumer nodes (Fig. 3). The milk producer nodes on the second rank led to a maximal further increase of the damage situation of 12.2% (Fig. 3 (a)). In contrast to the results for scenario with the inter-dairy trade, we always found the same milk producer node (ID: 100) on the first rank in all simulations in the scenario without inter-dairy trade (Fig. 3(b)). Moreover, three milk producer nodes were found in all 50 performed simulations, but on the ranks 2–5. All other 72 milk producer nodes were identified ten times on average in the simulations on the ranks 2–20.

A "direct neighborhood" ranking of milk producer nodes in the contingency plan without inter-dairy trade was identified for 63 (82.9%) nodes in all simulations (Fig. 3(b)).

The contingency plan without inter-dairy trade contained 29 milk producer nodes that were not included in the plan that took inter-dairy trade into account (Fig. 4(b)). These milk producer nodes were on average 7.7 times included in all simulations and were between ranks 2 and 19 in the rank-order. Conversely, 39 milk producer nodes existed in the contingency plan with inter-dairy trade that were not included in the plan without inter-dairy trade (Fig. 4(b)). These milk producer nodes had ranks between 1 and 9 in the rank-order and appeared on average 3.4 times in the

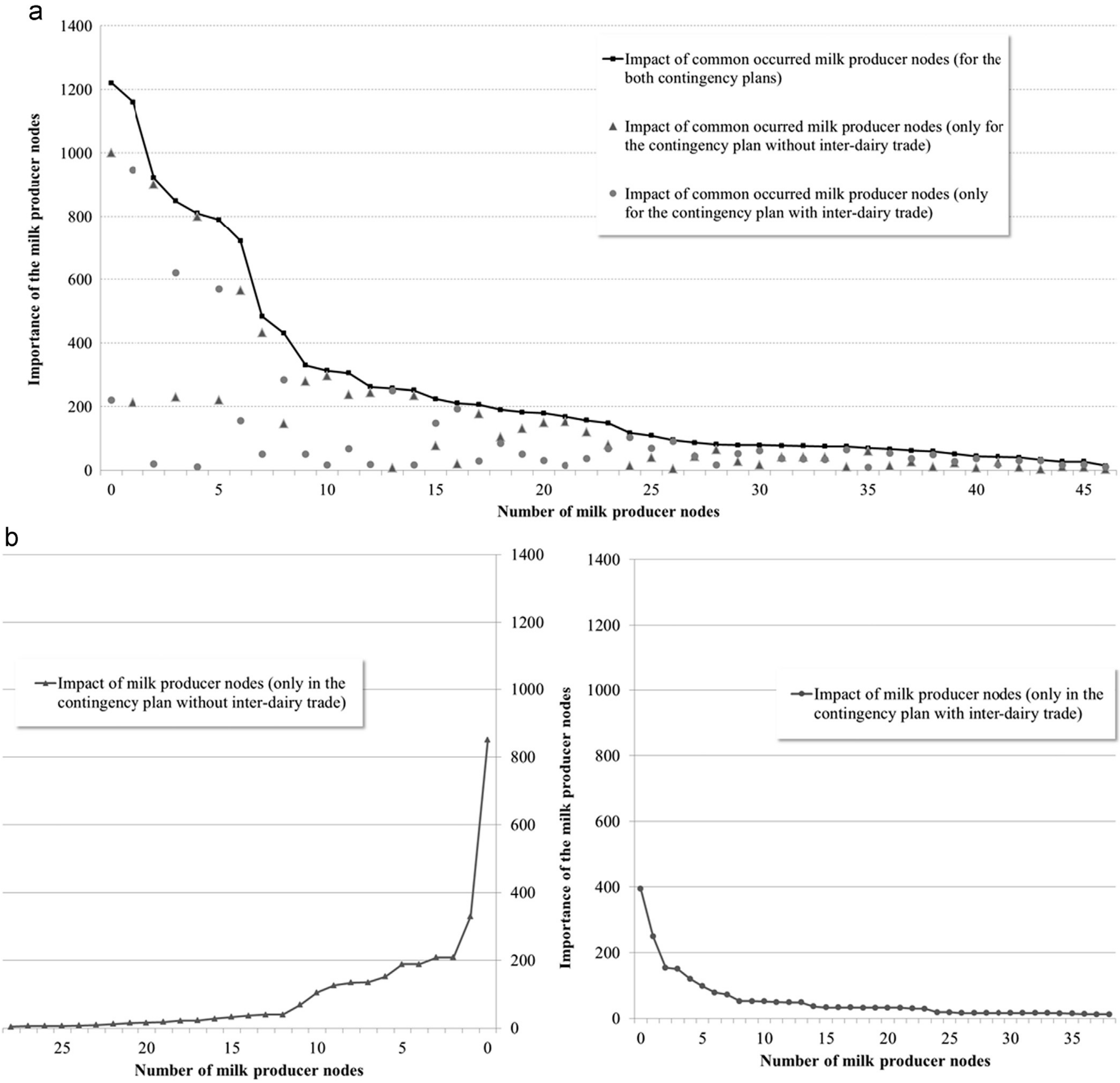


Fig. 4. Impact of milk producer nodes, (a) present in both contingency plans or (b) in only one of the contingency plans.

simulations. 64% of these milk producer nodes were involved twice at the maximum in all performed simulations.

In order to determine the impact of the milk producer nodes for a contingency plan, we used the maximum number of participating milk producer nodes ($r=20$) as obtained from the greedy-algorithm calculation (Fig. 3(b)). In this context, the maximum impact ($I_{\max}(p)$) of a milk producer in the contingency plan is 2000, if the milk producer node is identified on the first rank ($r_{\max}=20$) in all 100 simulations. Fig. 4(a) shows the common intersection of the both contingency plans. 47 (29.0%) of the milk producer nodes were present in both plans and therefore relevant regardless of the milk flow. The maximum impact of a milk producer node in the contingency plan was 1220 and the minimum 14. The average impact of the milk producer nodes was 260. If the impact of the common milk producer nodes in the contingency plan is compared separately for the trade flows with and without inter-dairy trade, it becomes clear that the milk producer nodes that have a high impact in the trade network without inter-dairy trade do not have the same level of importance for the trade flows with inter-dairy trade (Fig. 4(a)). No clear correlation ($R=0.013$) existed between these milk producer nodes regarding their impact on a damage situation. In this context, the milk producer nodes in the plan without inter-dairy trade had a 33.5% higher impact on the damage than the nodes in the list with inter-dairy trade.

Fig. 4(b) shows that the milk producer nodes in the contingency plan with inter-dairy trade possess on average half of the impact for a damage situation as the milk producer nodes in the contingency plan without inter-dairy trade.

4. Discussion

The assessment of the consequence of a deliberate or accidental release of a contamination in a food supply chain can only be done by computer simulation. The simulation results obtained in this study are only valid for the scenario described in the introduction and summarized in Eq. (1).

Confidential handling of data on supply structures related to deliberate contamination is important. This implies to realize the balancing act between creating knowledge for risk managers and to avoid creating instructions for an attack. On the one hand, the information provided for risk managers should answer the question "what should be done?" [52] in case of an attack or a threat of an attack. On the other hand, risk managers who use the results of simulation should understand the strengths and weaknesses of simulation results to avoid incorrect conclusions [53].

The strengths of simulations result from the fact that new insights for risk managers are provided, which cannot be offered by other means.

Our results showed that 60% of the milk producer nodes are not suitable as possible entry sources in our model because only 25.8% (without inter-dairy trade $n=76$) and 29.2% (with inter-dairy trade $n=86$) of the milk producer nodes as entry sources were identified in a total of 294 possible entry sources for each contingency plan. 29% of the milk producer nodes were present in both contingency plans and therefore relevant regardless of the milk flow. Especially the milk producer node with the ID 100 proved as important for risk managers because this milk producer node was found in 66 out of 100 simulations as the "best" milk producer node for a maximum spread of hypothetically contaminated milk. This milk producer represents a suitable entry source regardless of the flow of milk. Our findings indicate that cost- and time-efficient identification of such milk producer nodes (dairy farms) is possible if detailed trade data are used in the simulation. This may help risk managers to identify critical points with regard to the entry sources for a contamination in a food supply chain.

In addition, our research has proven that different trade structures have a significant impact on the number and the rank-order of selected entry sources for contaminations. Our hypothesis, that the number and the rank-order of milk producer nodes as entry sources for a contamination may vary due to the different trade flows of milk (Figs. 2 and 3(b)), was confirmed and can be underpinned by the following facts: First, the number of milk producer nodes as portals of entry for a pathogen to induce a worst-case situation varies within and between the contingency plans per simulation (min: 7|13; max: 15|20). The entry sources that exist regardless of the kind of trade, i.e. with or without inter-dairy trade (Fig. 4(a)), have a very different impact on the damage situation. It is not possible to tell that milk producer nodes identified as important in one of the contingency plans are also important in the other plan or vice versa. The simulations showed that trade between the dairies leads to a significant change of the potential entry sources for a contaminations. If the trade of milk between dairies is taken into account (Fig. 2(b)), more diversity at potential entry sources per rank-order becomes visible as compared to the list without inter-dairy trade (Fig. 3(b)). This observation can be underpinned by the fact that there were 50% more potential entry sources for contaminations on the first 13 ranks compared to the list of portals of entry for the network without inter-dairy trade (Figs. 2 and 3(b)). The consequence of this large number of entry sources for contaminations per rank is that no general statement can be made, which allows to select milk producer nodes that need to be monitored to mitigate the maximum damage. One consequence of a non-specific selection of the control points would be a delay in coping with the damage situation. In this context, a potential attacker runs a higher risk to select a milk producer node that is not relevant for the spread of the contamination as the selection is highly dependent on the respective milk trade flow, in contrast to the contingency plan without inter-dairy trade (Fig. 3(b)). Three milk producer nodes (ID: 100; 63; 47) appeared always on the same rank and on the first ranks in all simulations without inter-dairy trade. This means that a potential attacker could reach almost all consumer nodes via these entry sources. Milk producer nodes on the first rank can reach 68% of the consumer nodes (Fig. 3). The importance of these milk producer nodes as entry sources can be explained by the fact that these milk producer nodes delivered their milk to different dairy nodes. In a previous study it was shown that milk producer nodes delivered their milk on average to three different dairy nodes whereas some milk producer nodes delivered to up to 20 different dairy nodes [31]. Consequently, more trade connections in the milk trade network existed. If an attacker would choose a milk producer node from the first rank in the contingency plan with inter-dairy trade, 94% of consumer nodes could be reached. The importance of the milk producer nodes for the spread of the contamination in the inter-dairy trade network was shown by [32]. It was calculated that the spread of contaminated milk through some milk producer nodes could be higher if trade between dairy nodes existed. Generally, the importance of the inter-dairy trade for the spread of a contamination is illustrated by the fact that 30% of the total milk production in Germany is traded between dairies [31]. A detailed description of the German milk supply chain can be found in [31].

One of the limitations of the model results from the fact that the number of milk producer nodes not involved in the spread of a contamination in our model can be less than 60%, because the greedy algorithm cannot consider the theoretical case that two milk producer nodes may cause exactly the same extent of damage. In contrast to the model of Wein and Liu [13], our model does not include microbiology, processing, time-resolved delivery structures and compliance with existing security measures such as International Food Standard (IFS), British Retail Consortium (BRC) or Hazard Analysis and Critical Control Points (HACCP) etc., which may already exist at different levels of the milk supply chain and could influence the dimension of potential damage as well as the selection of the potential entry sources for contaminations. Another limitation is that the hypothetical attacker must process the complete data set to plan the attack beforehand and implement the scenario, which is unlikely in reality. A further limitation of this study is that the gravity model used to generate the trade network was only based on three variables (supply, demand and distances between actors), although it is well known that additional variables, such as the price of traded goods [44] are also important for the decision whether or not trade relations between actors take place [32]. An overview of the economic factors, which are essential for the choice of supplier partners in dairy industry, is given by [54]. Apart from economic factors, effects of terrorism on supplier selection require more attention [55]. Whereby, selection of supplier is a multi-criteria decision making [55–59].

However, it has been shown by this study that for the decision makers the type and number of trading partners can have a significant impact on the range of a damage situation. Furthermore, the suppliers, which should find more consideration in the operational-control-system of the dairies, were illustrated by means of the contingency plan. This information can influence the decision making in the supplier selection process. The surveillance activities for selected scenarios can be reduced by half by decision makers, if current data on trade flows are present. Nonetheless, it was shown in this work that an increased transparency or a high availability of data about the supply structure can lead to a maximal damage with minimal efforts based on the selection of suitable entry sources for a potential attacker. The protection of supplier data is essential in order to avoid such a scenario and therefore for food defense issues in the context of ERM.

Further research will focus on the kind of agencies or specific stages of the production process, which can influence the number of consumers reached, the kind of selected entry sources for a deliberate contamination and the assessment of the consequences related to deliberate contamination. This will be done with the help of the findings gained here.

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